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09/675,637	09/29/2000	Kenji Yamanishi	13931	1719

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SCULLY SCOTT MURPHY & PRESSER, PC
400 GARDEN CITY PLAZA
SUITE 300
GARDEN CITY, NY 11530

EXAMINER	
SHARON, AYAL I	

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Please find below and/or attached an Office communication concerning this application or proceeding.

Office Action Summary	**Application No.** 09/675,637	**Applicant(s)** YAMANISHI ET AL.
	Examiner Ayal I Sharon	**Art Unit** 2123

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If the period for reply specified above is less than thirty (30) days, a reply within the statutory minimum of thirty (30) days will be considered timely.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☒ Responsive to communication(s) filed on *16 September 2004*.

2a)☒ This action is **FINAL**. 2b)☐ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☒ Claim(s) *1-16* is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☒ Claim(s) *8 and 9* is/are allowed.

6)☒ Claim(s) *1-7 and 10-16* is/are rejected.

7)☒ Claim(s) *14* is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☐ The specification is objected to by the Examiner.

10)☒ The drawing(s) filed on *29 September 2000* is/are: a)☒ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☒ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☒ All b)☐ Some * c)☐ None of:

1.☒ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☐ Notice of References Cited (PTO-892)

2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)

3) ☐ Information Disclosure Statement(s) (PTO-1449 or PTO/SB/08) Paper No(s)/Mail Date _____.

4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____ .

5) ☐ Notice of Informal Patent Application (PTO-152)

6) ☐ Other: _____.

DETAILED ACTION

Introduction

1. Claims 1-16 of U.S. Application 09/675,637, originally filed on 09/29/2000 are presented for examination. In the amendment filed on 9/16/2004, the Applicants have amended claims 1-16.

Claim Objections

2. Claim 14 is objected to because of the following informalities: "said histogram calculation method" is repeated twice in lines 4-5. Appropriate correction is required.

Claim Rejections - 35 USC § 101

3. 35 U.S.C. 101 reads as follows:

> Whoever invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a patent therefor, subject to the conditions and requirements of this title.

4. Claims 10-16 are rejected under 35 U.S.C. 101 because the claimed invention is directed to non-statutory subject matter. The claims, as written, are directed to an abstract mathematical algorithm which is not implemented in the technological arts (e.g. embodied in a computer or on a computer readable medium). The claimed invention is therefore not concrete or tangible. See MPEP §2106 (A),

and *In re Warmerdam*, 33 F.3d 1354, 1360, 31 USPQ2d 1754, 1759 (Fed. Cir. 1994). See also *Schrader*, 22 F.3d at 295, 30 USPQ2d at 1459.

Claim Rejections - 35 USC § 102

5. The following is a quotation of the appropriate paragraphs of 35 U.S.C. 102 that form the basis for the rejections under this section made in this Office action:

A person shall be entitled to a patent unless –

(b) the invention was patented or described in a printed publication in this or a foreign country or in public use or on sale in this country, more than one year prior to the date of application for patent in the United States.

6. The prior art used for these rejections is as follows:
7. Burge, P. and Shawne-Taylor, J. "Detecting Cellular Fraud Using Adaptive Prototypes". Proc. of AI Approaches to Fraud Detection and Risk Management. Pp.72-77, 1997. (Henceforth "**Burge**").
8. Yamanishi, K. et al. "On-line Unsupervised Outlier Detection Using Finite Mixtures With Discounting Learning Algorithms." Proc. of the 6th ACM SIGKDD Int'l Conf. on Knowledge Discovery and Data Mining. Pp.320-324. 2000. (Henceforth "**Yamanishi**").
9. Examiner notes that the model in the Yamanishi reference maps to the model in the current application - for example, compare the following equations:
   (a) Equation in Specification, p.24, line 5, to Equation in Burge, p.321, col.2, "Gaussian Mixture Model", net-to-last equation.
   (b) Equation in Specification, p.24, line 8, to Equation in Burge, p.321, col.2, last equation.

(c) Equations in Specification, p.26, to Equations in Burge, p.322, col.2, "SDEM Algorithm".

(d) Equation in Specification, p.29, line 15 to Equation in Burge, p.322, col.2, "kernel mixture model" Eq.3.

(e) Equation In Specification, p.39, line 16, to Equation in Burge, p.323, col.1, "logarithmic loss", last equation.

10. Examiner notes that the Applicants have admitted (Specification, p.3, paragraph 2) that the Burge reference "... relates a similar fraud detection based on unsupervised data ...", and the Yamanishi reference teaches that the model that it discloses " ... was inspired by the work by Burge and Shawe-Taylor."

11. The claim rejections are hereby summarized for Applicant's convenience. The detailed rejections follow.

12. Claims 1-7 and 10-16 are rejected under 35 U.S.C. 102(b) as being clearly anticipated by Burge.

13. In regards to Claim 1, Burge teaches the following limitations:

1. <u>A probability density estimation device for an anomalous data detection system adapted to detect anomalous data, said probability density estimation device configured for</u>
a degree of outlier calculation device
for sequentially calculating a degree of outlier of each
data with a data sequence of real vector values as input,
<u>said</u> probability density estimation device for,
while sequentially reading said data sequence, estimating a
probability distribution of generation of the data in
question by using a finite mixture distribution of
normal distributions, <u>said probability density estimation device</u> comprising:
(Burge, especially: "Protoyping")

probability calculation means for calculating,
based on a value of input data and values of a mean
parameter and a variance parameter of each of a finite
number of normal distribution densities, a probability of
generation of the input data in question

from each normal distribution; and
(Burge, especially: "Constructing Profiles")

parameter output means for updating and rewriting the stored parameter values while forgetting past data, according to newly read data based on a probability obtained by the probability calculation means, values of a mean parameter and a variance parameter of each normal distribution and a weighting parameter of each normal distribution.
(Burge, especially: "The Fraud Engine")

14. In regards to Claim 2, Burge teaches the following limitations:

2. The probability density estimation device as set forth in claim 1, further comprising:

parameter storage means for storing values of a mean parameter and a variance parameter of each of a finite number of normal distribution densities and a weighting parameter of each normal distribution, wherein
(Burge, especially: "Constructing Profiles")

said parameter rewriting means updates and rewrites data of said parameter storage means.
(Burge, especially: "Constructing Profiles")

15. In regards to Claim 3, Burge teaches the following limitations:

3. A degree of outlier calculation device for sequentially calculating a degree of outlier of each data with a data sequence of real vector values as input, said degree of outlier calculation device adapted to detect anomalous data, and comprising:

a probability density estimation device for, while sequentially reading said data sequence, estimating a probability distribution of generation of the data in question by using a finite mixture of normal distributions, said probability density estimation device including
(Burge, especially: "Constructing Profiles")

(a) parameter storage means for storing values of a mean parameter and a variance parameter of each of a finite number of normal distribution densities and a weighting parameter of each normal distribution;
(Burge, especially: "Constructing Profiles")

(b) probability calculation means for calculating, based on a value of input data and values of a mean parameter and a variance parameter of each of a finite number of normal distribution densities, a probability of generation of the input data in question

from each normal distribution; and
(Burge, especially: "Constructing Profiles")

(c) parameter rewriting means for updating and rewriting the stored parameter values while forgetting past data, according to newly read data based on a probability obtained by the probability calculation means, values of a mean parameter and a variance parameter of each normal distribution and a weighting parameter of each normal distribution; and
(Burge, especially: "Constructing Profiles")

degree of outlier calculation means for calculating and outputting a degree of outlier of said data by using a parameter of the normal mixture updated by said probability density estimation device and based on a probability distribution estimated from values of the parameters before and after the updating and the input data.
(Burge, especially: "The Fraud Engine")

16. In regards to Claim 4, Burge teaches the following limitations:

4. A probability density estimation device for use in a degree of outlier calculation device adapted for anomalous data detection, the degree of outlier calculation device for , while sequentially reading a data sequence, estimating a probability distribution of generation of the data in question by using a finite mixture distribution of kernel distributions, the probability density estimation device comprising:

parameter storage means for storing a value of a parameter indicative of a position of each kernel, and
(Burge, especially: "Constructing Profiles")

parameter output means for reading a value of a parameter from the parameter storage means and updating the stored parameter values while forgetting past data, according to newly read data, to rewrite the contents of the parameter storage means.
(Burge, especially: "Constructing Profiles")

17. In regards to Claim 5, Burge teaches the following limitations:

5. A degree of outlier calculation device for sequentially calculating a degree of outlier of each data with a data sequence of real vector values as input, said degree of outlier calculation device adapted for anomalous data detection, and comprising:

a probability density estimation device for, while sequentially reading said data sequence, estimating a probability distribution of generation of the data in question by using a finite

mixture distribution of kernel distributions, the probability density estimation device including
(Burge, especially: "Constructing Profiles")

(a) parameter storage means for storing a value of a parameter indicative of a position of each kernel; and
(Burge, especially: "Constructing Profiles")

(b) parameter rewriting means for reading a value of a parameter from the storage means and updating the stored parameter values while forgetting past data, according to newly read data to rewrite the contents of the parameter storage means, and
(Burge, especially: "Constructing Profiles")

degree of outlier calculation means for calculating and outputting a degree of outlier of said data by using said parameter updated by said probability density estimation device and based on a probability distribution estimated from values of the parameters before and after the updating and the input data.
(Burge, especially: "The Fraud Engine")

18. In regards to Claim 6, Burge teaches the following limitations:

6. A histogram calculation device for a degree of outlier calculation device for sequentially calculating a degree of outlier of each data with discrete value data as input, said degree of outlier calculation device useful for anomalous data detection, histogram calculation device for calculating a parameter of a histogram with respect to said discrete value data sequentially input, said histogram calculation device comprising:

storage means for storing a parameter value of said histogram; and
(Burge, especially: "Constructing Profiles")

parameter updating means for reading said parameter value from the storage means and updating past parameter values while forgetting past data based on input data to rewrite the value of said storage means, thereby outputting some of parameter values of said storage means.
(Burge, especially: "Constructing Profiles")

19. In regards to Claim 7, Burge teaches the following limitations:

7. A degree of outlier calculation device for sequentially calculating a degree of outlier of each data with discrete value data as input, said degree of outlier calculation device useful for anomalous data detection, and comprising:

a histogram calculation device for calculating a parameter of a histogram with respect to said discrete

value data sequentially input, said histogram calculation device including
(Burge, especially: "Constructing Profiles")

storage means for storing a parameter value of said histogram, and
(Burge, especially: "Constructing Profiles")

parameter updating means for reading said parameter value from the storage means and updating past parameter values while forgetting past data based on input data to rewrite the value of said storage means, thereby outputting some of parameter values of said storage means; and
(Burge, especially: "Constructing Profiles")

score calculation means for calculating, based on the output of the histogram calculation device and said input data, a score of the input data in question with respect to said histogram, thereby outputting the output of the score calculation means as a degree of outlier of said input data.
(Burge, especially: "The Fraud Engine")

20. In regards to Claim 10, Burge teaches the following limitations:

10. A probability density estimation method for a degree of outlier calculation device for sequentially calculating a degree of outlier of each data with a data sequence of real vector values as input, said degree of outlier calculation device useful for anomalous data detection, said probability density estimation method of, while sequentially reading said data sequence, estimating a probability distribution of generation of the data in question by using a finite mixture of normal distributions, the method comprising:
(Burge, especially: "Constructing Profiles")

based on values of a mean parameter and a variance parameter of each of a finite number of normal distribution densities read from parameter storage means for storing a value of input data, values of a mean parameter and a variance parameter of each of a finite number of normal distribution densities, and a weighting parameter of each normal distribution, calculating a probability of generation of the input data in question from each normal distribution; and
(Burge, especially: "Constructing Profiles")

updating the stored parameter values while forgetting past data, according to newly read data based on a probability obtained by the probability calculation means, values of a mean parameter and a variance parameter of each normal distribution and a weighting parameter of each

normal distribution to rewrite data of said parameter storage means.
(Burge, especially: "Constructing Profiles")

21. In regards to Claim 11, Burge teaches the following limitations:

11. A method of sequentially calculating a degree of outlier of each data, with a data useful for anomalous data detection, sequence of real vector values as input, including a probability density estimation for, while sequentially reading said data sequence, estimating a probability distribution of generation of the data in question by using a finite mixture of normal distributions, comprises the probability density estimation comprising:
(Burge, especially: "Constructing Profiles")

based on values of a mean parameter and a variance parameter of each of a finite number of normal distribution densities read from parameter storage means for storing a value of input data, values of a mean parameter and a variance parameter of each of a finite number of normal distribution densities, and a weighting parameter of each normal distribution, calculating a probability of generation of the input data in question from each normal distribution, and
(Burge, especially: "Constructing Profiles")

updating the stored parameter values while forgetting past data, according to newly read data based on a probability obtained by the probability calculation means, values of a mean parameter and a variance parameter of each normal distribution and a weighting parameter of each normal distribution to rewrite data of said parameter storage means; said method sequentially calculating a degree of outlier of each data further comprising:
(Burge, especially: "Constructing Profiles")

calculating and outputting a degree of outlier of said data by using a parameter of the finite mixture distribution updated by said probability density estimation and based on a probability distribution estimated from values of the parameters before and after the updating and the input data.
(Burge, especially: "The Fraud Engine")

22. In regards to Claim 12, Burge teaches the following limitations:

12. A probability density estimation method for use in calculation of a degree of outlier useful for anomalous data detection to, while sequentially reading a data sequence, estimate a probability distribution of generation of the data in question by using a finite mixture distribution of kernel distributions, said probability density estimation method comprising the steps of:
(Burge, especially: "Constructing Profiles")

storing a value of a parameter indicative of a position of each kernel in parameter storage means, and

reading a value of a parameter from the storage means and updating the stored parameter values while forgetting past data, according to newly read data to rewrite the contents of the parameter storage means.

(Burge, especially: "Constructing Profiles")

23. In regards to Claim 13, Burge teaches the following limitations:

13. A degree of outlier calculation method of sequentially calculating a degree of outlier of each data, <u>said degree of outlier calculation method useful for anomalous data detection,</u> with a data sequence of real vector values as input, wherein

probability density <u>is estimated </u>for, while sequentially reading said data sequence, estimating a probability distribution of generation of the data in question by using a finite <u>mixture distribution of kernel</u> distributions <u>the degree of outlier calculation method comprising</u>:

(Burge, especially: "Constructing Profiles")

storing a value of a parameter indicative of a position of each kernel in parameter storage means;

(Burge, especially: "Constructing Profiles")

reading a value of a parameter from the storage means and updating the stored parameter values while forgetting past data, according to newly read data to rewrite the contents of the parameter storage means, <u>the parameter storage means including</u>:

(Burge, especially: "Constructing Profiles")

degree of outlier calculation means for calculating and outputting a degree of outlier of said data by using said parameter updated by said probability density estimation and based on a probability distribution estimated from values of the parameters before and after the updating and the input data.

(Burge, especially: "The Fraud Engine")

24. In regards to Claim 14, Burge teaches the following limitations:

14. <u>A histogram calculation method for</u> use in calculation of a degree of outlier for sequentially calculating a degree of outlier of each data with discrete value data as input, <u>said calculation of the degree of outlier useful for anomalous data detection, said histogram calculation method, said</u> histogram calculation method of calculating a parameter of a histogram with respect to said discrete value data sequentially input, comprising the steps of:

reading said parameter value from storage means for storing a parameter value of said histogram and updating past parameter values while forgetting past data based on input data to rewrite the value of said storage means; and

(Burge, especially: "Constructing Profiles")

outputting some of parameter values of said storage means.

(Burge, especially: "Constructing Profiles")

25. In regards to Claim 15, Burge teaches the following limitations:

15. A degree of outlier calculation device for sequentially calculating a degree of outlier of each data with discrete value data as input, said degree of outlier calculation device useful for detecting anomalous data, and comprising:

a histogram calculation device for calculating a parameter of a histogram with respect to said discrete value data sequentially input including:

(Burge, especially: "Constructing Profiles")

storage means for storing a parameter value of said histogram; and

(Burge, especially: "Constructing Profiles")

parameter updating means for reading said parameter value from the storage means and updating past parameter values while forgetting past data based on input data to rewrite the value of said storage means, thereby outputting some of parameter values of said storage means; and

(Burge, especially: "Constructing Profiles")

score calculation means for calculating, based on the output of the histogram calculation device and said input data, a score of the input data in question with respect to said histogram, thereby outputting the score calculation result as a degree of outlier of said input data.

(Burge, especially: "The Fraud Engine")

26. In regards to Claim 16, Burge teaches the following limitations:

16. A degree of outlier calculation method of calculating a degree of outlier with respect to sequentially input data which is described both in a discrete value and a continuous value, calculation of the degree of outlier useful for detection of anomalous data, wherein a

histogram calculation estimates a histogram with respect to a discrete value data part, said method comprising the steps of:
(Burge, especially: "Constructing Profiles")

reading said parameter value from storage means for storing a parameter value of said histogram and updating past parameter values while forgetting past data based on input data to rewrite the value of said storage means; and
(Burge, especially: "Constructing Profiles")

outputting some of parameter values of said storage means, and wherein
(Burge, especially: "Constructing Profiles")

probability density estimation devices provided as many as the number of cells of said histogram for estimating a probability density with respect to a continuous value data part, said method comprises the steps of:
(Burge, especially: "Constructing Profiles")

based on values of a mean parameter and a variance parameter of each of a finite number of normal distribution densities read from parameter storage means for storing a value of input data, values of a mean parameter and variance parameter of each of a finite number of normal distribution densities and a weighting parameter of each normal distribution, calculating a probability of generation of the input data in question from each normal distribution; and
(Burge, especially: "Constructing Profiles")

based on a probability obtained by the probability calculation means, values of a mean parameter and a variance parameter of each normal distribution and a weighting parameter of each normal distribution, updating the stored parameter values while forgetting past data, according to newly read data to rewrite the data of said parameter storage means;
(Burge, especially: "Constructing Profiles")

determining to which cell of said histogram said discrete value data part belongs to send the continuous data part to the corresponding one of said probability density estimation devices;
(Burge, especially: "Constructing Profiles")

calculating a score of said input data based on a probability distribution estimated from output values of

said histogram calculation device and said probability density estimation device and said input data; and
(Burge, especially: "The Fraud Engine")

outputting the score calculation result as a degree of outlier of said input data.
(Burge, especially: "The Fraud Engine")

Allowable Subject Matter

27. Claims 8 and 9 are allowed.

28. The closest relevant prior art is as follows:

a. Burge, P. and Shawne-Taylor, J. "Detecting Cellular Fraud Using Adaptive Prototypes". Proc. of AI Approaches to Fraud Detection and Risk Management. Pp.72-77, 1997. (Henceforth "**Burge**").

b. Yamanishi, K. et al. "On-line Unsupervised Outlier Detection Using Finite Mixtures With Discounting Learning Algorithms." Proc. of the 6th ACM SIGKDD Int'l Conf. on Knowledge Discovery and Data Mining. Pp.320-324. 2000. (Henceforth "**Yamanishi**").

29. The Yamanishi reference, which post-dates the foreign priority date of the application, is relevant in regards to its discussion of the Burge reference (See MPEP §2128 and *In re Epstein*, 32 F.3d 1559, 31 USPQ2d 1817 (Fed. Cir. 1994)).

30. Examiner notes that two of the three co-authors of the Yamanishi article are the inventors in the present application.

31. The Yamanishi reference (See p.320, col.2, para. 3) teaches the following about the Burge reference:

> Note that there exists only a few works (e.g. Burge) focusing on the on-line unsupervised learning based approach [to outlier detection in data mining].

and also specifies three differences between the Burge model the Yamanishi model (See p.321, col.1, para.5) :

> The design of SS [SmartSifter] was inspired by the work by Burge and Shawe-Taylor. Our work differs from [Burge] in the following regards:
>
> 1) SS [SmartSifter] treats both categorical and continuous variables, while [Burge] deals only with continuous ones.
>
> 2) While Burge uses two models in the algorithm: the long term model and the short term one, SS [SmartSifter] unifies them into one model with the aim of a clearer statistical meaning and a lower computational cost.
>
> 3) SS [SmartSifter] uses either a parametric representation for a probabilistic model or a non-parametric one, while only a non-parametric one is used in [Burge]. In Sec.3.1, we compare our parametric method with the non-parametric one to show that the former outperforms the latter both in accuracy and computation costs.

32. Moreover, Applicant's own admission (Specification, p.3, paragraphs 2-3) regarding the Burge reference is:

> The method by P. Burge and J. Shawe-Taylor relates to a similar fraud detection based on unsupervised data. This method, however, conducts fraud detection with two non-parametric models, a short-term model and a long-term model, to make a distance between them as a criterion for an outlier. Statistical basis of the short-term model and the long-term model is insufficient to make statistical significance of a distance therebetween [sic] unclear.
>
> In addition, preparation of two models, short-term and long-terms [sic], deteriorates calculation efficiency. Further problems are involved such as a problem that only continuous value data can be handled and not categorical data and a problem that since only non-parametric models are handled, fraud detection is unstable and inefficient.

33. Applicants persuasively argue (see amendment filed 9/16/2004, pp.22-23) regarding claims 8 and 9 that:

a. "With respect to independent claims 8 and 10, these claims require, *inter alia*, 'data which is described both in a discrete value and a continuous value' and 'mean parameter', 'variance parameter' and 'weighting parameter.' Thus, these claims require a parametric and unitary model handling both continuous variables and categorical variables. Therefore, Burge does not disclose or suggest the recitations of independent claims 8 and 10."

b. "Independent claim 9 requires, *inter alia*, 'data which is described both in a discrete value and a continuous value', 'estimating a histogram with respect to said discrete value data part' and 'estimating a probability density with respect to a continuous value data part." Thus, claim 9 requires a parametric and unitary model handling both continuous variables and categorical variables. Therefore, Burge does not disclose or suggest the recitations of independent claim 9."

34. Examiner therefore finds claims 8 and 9 to be allowable.

Response to Amendment

Re: Oath/Declaration

35. Examiner finds Applicants' clarification (amendment filed 9/16/2004, pp.17-18) regarding the involvement of Mr. Williams's and Mr. Milne's role in the present invention to be persuasive, and has withdrawn the objection to the declaration.

Re: Claim Objections

36. Examiner finds that Applicants' amendment (filed 9/16/2004) to Claims 1, 6, 10, and 14 overcomes the objections raised in the previous Office Action: that the

awkward phrasing of the claims made it difficult to determine whether the claims are method claims or device claims. The objections have been withdrawn.

Re: Double Patenting

37. Examiner has accepted Applicants' persuasive arguments in the amendment (filed 9/16/2004, pp.19-20) regarding the Double Patenting rejections in view of co-pending Application No. 10/179,374 and 10/619,626. These rejections have been withdrawn.

Re: 35 USC § 101

38. Examiner has partially accepted Applicants' arguments in the amendment (filed 9/16/2004, pp.18-19) regarding the 35 USC § 101 rejections.
39. The rejections of all claims (Claims 1-16) on the grounds of a lack of a specific and substantial asserted utility or a well established utility have been withdrawn. The specification (p.4) refers to practical utility of fraud detection.
40. Moreover, the rejections of the device claims (Claims 1-9) on the grounds of non-statutory subject matter have also been withdrawn.
41. The rejections of the method claims (Claims 10-16) on the grounds of non-statutory subject matter, however, are being maintained because they are directed to an abstract mathematical algorithm.

Re: 35 USC § 112

42. Examiner has accepted Applicants' arguments in the amendment (filed 9/16/2004, pp.18-19) regarding the 35 USC § 112 rejections.

43. The rejections of all claims (Claims 1-16) on the grounds of a lack of a specific and substantial asserted utility or a well established utility have been withdrawn. The specification (p.4) refers to practical utility of fraud detection.

Re: 35 USC § 102

44. The Yamanishi reference (See p.320, col.2, para. 3) teaches the following about the Burge reference:

> Note that there exists only a few works (e.g. Burge) focusing on the on-line unsupervised learning based approach [to outlier detection in data mining].

and also the following (See p.321, col.1, para.5) about the Burge reference:

> The design of SS [SmartSifter] was inspired by the work by Burge and Shawe-Taylor. Our work differs from [Burge] in the following regards:
>
> 1) SS [SmartSifter] treats both categorical and continuous variables, while [Burge] deals only with continuous ones.
>
> 2) While Burge uses two models in the algorithm: the long term model and the short term one, SS [SmartSifter] unifies them into one model with the aim of a clearer statistical meaning and a lower computational cost.
>
> 3) SS [SmartSifter] uses either a parametric representation for a probabilistic model or a non-parametric one, while only a non-parametric one is used in [Burge]. In Sec.3.1, we compare our parametric method with the non-parametric one to show that the former outperforms the latter both in accuracy and computation costs.

45. In the previous Office Action, the Examiner indicated that these features, if amended into the claims, would differentiate the current application from the prior art. However, in the recent amendment (filed 9/16/2004), Applicants have not expressly amended these limitations into the rejected claims.

46. Applicants unpersuasively argue (amendment filed 9/16/2004, pp.22-23) that:

   a. "... independent claims 1 and 3 require, *inter alia,* 'mean parameter', 'variance parameter' and 'weighting parameter' of a finite mixture distribution of normal distributions. Thus, claims 1 and 3 require a parametric and unitary model."

   b. "Independent claims 4, 5, 12 and 13 require, *inter alia*, 'a finite mixture distribution of kernel distributions.' Thus, claims 4, 5, 12 and 13 require a unitary model. Therefore, Burge does not disclose or suggest the recitations of independent claims 4, 5, 12 and 13."

   c. "Independent claims 6, 7, 14 and 15 require, *inter alia*, 'discrete value data as input' and 'histogram.' Thus, independent claims 6, 7, 14 and 15 require that a parametric and unitary model is used treating categorical variables. Therefore, Burge does not disclose or suggest the recitations of independent claims 6, 7, 14 and 15."

Examiner respectfully disagrees with Applicants' conclusory statements, which do not provide any reasoning behind their conclusions. The rejections are therefore maintained.

Conclusion

47. Applicant's amendment necessitated the new ground(s) of rejection presented in this Office action. Accordingly, **THIS ACTION IS MADE FINAL.** See MPEP § 706.07(a). Applicant is reminded of the extension of time policy as set forth in 37 CFR 1.136(a).

A shortened statutory period for reply to this final action is set to expire THREE MONTHS from the mailing date of this action. In the event a first reply is filed within TWO MONTHS of the mailing date of this final action and the advisory action is not mailed until after the end of the THREE-MONTH shortened statutory period, then the shortened statutory period will expire on the date the advisory action is mailed, and any extension fee pursuant to 37 CFR 1.136(a) will be calculated from the mailing date of the advisory action. In no event, however, will the statutory period for reply expire later than SIX MONTHS from the date of this final action.

Correspondence Information

Any inquiry concerning this communication or earlier communications from the examiner should be directed to Ayal I. Sharon whose telephone number is (571) 272-3714. The examiner can normally be reached on Monday through Thursday, and the first Friday of a biweek, 8:30 am – 5:30 pm.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Kevin Teska can be reached at (571) 272-3716.

Any response to this office action should be faxed to (703) 872-9306, or mailed to:

USPTO
P.O. Box 1450
Alexandria, VA 22313-1450

or hand carried to:

USPTO
Customer Service Window
Randolph Building
401 Dulany Street
Alexandria, VA 22314

Any inquiry of a general nature or relating to the status of this application or proceeding should be directed to the Tech Center 2100 Receptionist, whose telephone number is (571) 272-2100.

Ayal I. Sharon

Art Unit 2123

February 22, 2005

KEVIN J. TESKA
SUPERVISORY
PATENT EXAMINER